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Flocks, Swarms, Crowds, and Societies: On the Scope and Limits of Cognition

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FLOCKS, SWARMS, CROWDS, AND SOCIETIES:
ON THE SCOPE AND LIMITS OF COGNITION

by

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A thesis submitted in partial fulfillment of the requirements
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Thesis Chair: Dr. Luis H. Favela

“One wonders what the computationalists do with the simple reality that minds, as they currently exist on the face of the earth, are most surely organic processes and are in some deep and perhaps essential way grounded in non-mental organic processes” (Gallagher, 2008, p. 19).

ABSTRACT

Traditionally, the concept of cognition has been tied to the brain or the nervous system. Recent work in various noncomputational cognitive sciences has enlarged the category of “cognitive phenomena” to include the organism and its environment, distributed cognition across networks of actors, and basic cellular functions. The meaning, scope, and limits of ‘cognition’ are no longer clear or well-defined. In order to properly delimit the purview of the cognitive sciences, there is a strong need for a clarification of the definition of cognition. This paper will consider the outer bounds of that definition. Not all cognitive behaviors of a given organism are amenable to an analysis at the organismic or organism-environment level. In some cases, emergent cognition in collective biological and human social systems arises that is irreducible to the sum cognitions of their constituent entities. The group and social systems under consideration are more extensive and inclusive than those considered in studies of distributed cognition to date. The implications for this ultimately expand the purview of the cognitive sciences and bring back a renewed relevance for anthropology and introduce sociology on the traditional six-pronged interdisciplinary wheel of the cognitive sciences.

Keywords: social cognition; animal cognition; 4EA cognition; systems science

DEDICATION

To Dr. Favela: In gratitude and admiration.

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CHAPTER 1: INTRODUCTION

Not all cognitive behaviors of a given organism are amenable to an analysis at the organismic or organism-environment level. In some cases, emergent cognition in collective biological and human social systems arises that is irreducible to the sum cognitions of their constituent entities. The term ‘social cognition’ generally captures the broad phenomena under consideration.¹ Social cognition is usually conceived of reductively as an interaction between the cognition of individual agents. A brief introduction to the problem of the borders of cognition is first given. Next, two key terms are defined: CRUM and 4EA cognition. The approach of this paper is then defined in relation to 4EA cognition. Next, the method used for the discovery of the upper bounds of cognition is outlined. A taxonomy of social cognition is then presented, including three types of nonreductive social cognition: distributed cognition, swarm intelligence, and superorganismic cognition. Finally, a series of case studies in collective biological and human social systems is presented. They include systems far larger and more extensive than have previously been considered under the heading of social cognition. Ultimately, presenting these cases as cognitive systems serves to expand the bounds of “cognition.”

1.1 The Problem: The Bounds of Cognition

The cognitive sciences are in the midst of a scientific revolution. The cognitive revolution began over half a century ago, establishing the dominance of the computational-representational understanding of mind (CRUM). “Cognition” was generally accepted as referring to higher-order

¹ Social cognition is not an approach to cognition akin to connectionism, embodied cognition, or extended cognition. It merely designates cognition that occurs in groups.

thought, such as language, logic, and problem-solving. The borders of cognition were seemingly intuitive, starting and ending in the brain or nervous system. Today, this orthodoxy is facing challenges on multiple fronts. Multiple competing theoretical and experimental paradigms are being developed that question both the meaning and the extent of cognition. Basic intuitions about cognition are being subjected to critique and it is no longer certain precisely where the bounds of cognition lie. Multiple approaches—sometimes mutually incompatible—now compete for dominance and neither its upper nor lower bounds are clearly defined. The aim of this study is to demonstrate that emergent cognition occurs in collective biological and human social systems in order to delimitate the outer limits of cognition.

For CRUM, cognition is localizable in the brain or the nervous system of an individual organism. Part of the intuitiveness of this idea stems from the historical dominance of CRUM itself. Throughout history, different loci of the mind or cognition have been considered to be intuitive. The heart has been considered as such a locus by civilizations as diverse as ancient Greece, India, and China (Lind, 2007). Many of the new approaches to cognition pose a challenge to that well-defined and intuitive border. Enactivism posits that microscopic, autopoietic bacteria are primitive cognitive systems (Maturana & Varela, 1980). Extended cognition, as its name suggests, posits cognition as extending beyond the brain and into specific tools in the world (Clark & Chalmers, 1998). Distributed cognition posits cognition as a property of social and technical systems, such as a navy ship (Hutchins, 1995a) or the Hubble Space Telescope (HST; Giere, 2006). Embodied cognition posits cognition as anywhere from being influenced by a body to being in principle inseparable from it. Radical embodied cognitive science (RECS) posits cognition as an emergent property of an organism-environment system

(Chemero, 2009). Radical embodied cognitive neuroscience RECN posits cognition as a systems-level property of a nervous system-organism-environment system (Favela, 2014). Across these multiple perspectives, cognition has been variously localized in systems as small as microscopic bacteria and as large as a ship, an airplane cockpit, or the HST. It possibly extends even beyond that. Unlike with CRUM, none of these conceptions are particularly intuitive. This makes conceptualization particularly difficult and controversial. The entire range of cognitive phenomena, from the inner bounds of the minimally-cognitive to the outer bounds of the maximally-cognitive, is here defined as the “noosphere.”² It is the set of all cognitive systems.

1.2 The Historical Background: The Cognitive Revolution in Revolt

The cognitive sciences formally emerged as a discipline—or more precisely as an interdisciplinary nexus of disciplines—from the cognitive revolution in psychology. From the 1920s until the late 1950s, experimental psychology in the United States was dominated by behaviorism. In 1956, two conferences forever changed the historical course of psychology. At Dartmouth, the Summer Research Project on Artificial Intelligence convened to determine how to utilize the new computer technology to create artificial intelligence. That September, the Symposium of Information Theory was held at MIT. George A. Miller there presented his now legendary paper on the capacity of short-term memory, effectively undermining the behaviorist assumption that the mind could not be studied empirically (1956). Inspired by the Dartmouth

² The concept of the noosphere was introduced by Teilhard de Chardin (1955/2008) to describe the range of “higher” cognitive functions and consciousness. Here, the term is appropriated to describe the entire range of cognitive phenomena, “higher” and “lower,” without reference to consciousness.

conference, Herb Simon and Alan Newell developed Logic Theorist as the first practical AI system. During this *annus mirabilis*, the cognitive revolution, or modern computationalism, was born.³

The cognitive revolution did not develop in a cultural, scientific, and technological vacuum. Several developments set up the preconditions for the new computational outlook of the two conferences of 1956. In the 1930s, Edward Tolman began challenging behaviorist epistemology with his introduction of the concept of the “cognitive map.” Although himself a behaviorist, he argued that rats navigate through mazes using mental representations of spaces, or cognitive maps. Such a mentalistic explanation was forbidden territory for behaviorists, but his work nevertheless achieved empirical rigor. In the 1930s and 40s, Alan Turing developed the Turing machine, one of the first theories of serial computing. In 1945, John von Neumann introduced von Neumann architecture, an abstract flow diagram for computer architecture (see Figure 1). Notably, he saw the computer as an analogical model of the brain (Neumann, 1993). In the late 1930s and early 1940s, Horst Zuse developed the Z1, Z2, and Z3 computers in Germany. In 1942, John Atanasoff and his student Clifford Berry produced the ABC, also known as the Atanasoff-Berry computer. During the Second World War, the British developed the Bombe to decode the German Enigma codes. IBM completed ENIAC, the first major digital computer, soon after the end of the Second World War (O'Regan, 2012).

³ Computationalism itself dates back to Thomas Hobbes and its model was arithmetic (Chemero, 2009). Modern computationalism is CRUM and its model is the serial computer.

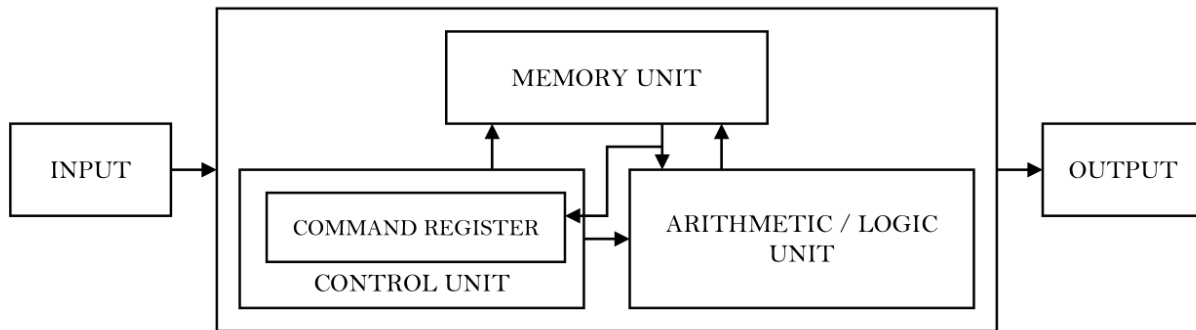


Figure 1. A flow diagram of von Neumann architecture, first described in von Neumann (1993). Adapted from Rojas & Hashagen (2000, p. 77).

Noam Chomsky and Donald Broadbent were two further major contributors to the cognitive revolution. Chomsky spearheaded the cognitive approach to linguistics with his generative grammar. Beginning in 1956, he began to bring a new “precision of mathematics” to linguistics countering the nebulous behaviorist theory of reinforcement (Miller, 2003). This exploratory work was formalized in 1957 in his *Syntactic Structures*. A year later, Donald Broadbent developed the first testable model of the mind (1958). Inspired by serial processing models of computing, Broadbent developed a flow diagram for his filter theory of attention and hence created the first mental module (see Figure 2). The influence of the emerging computer technology and the mathematics of information processing on this model is evident (cf. Figure 1). Just as hydraulic technology once inspired Descartes’ model of the brain (Hoffman, Cochran, & Nead, 1990), the computer inspired the nascent computationalism of the 1950s.

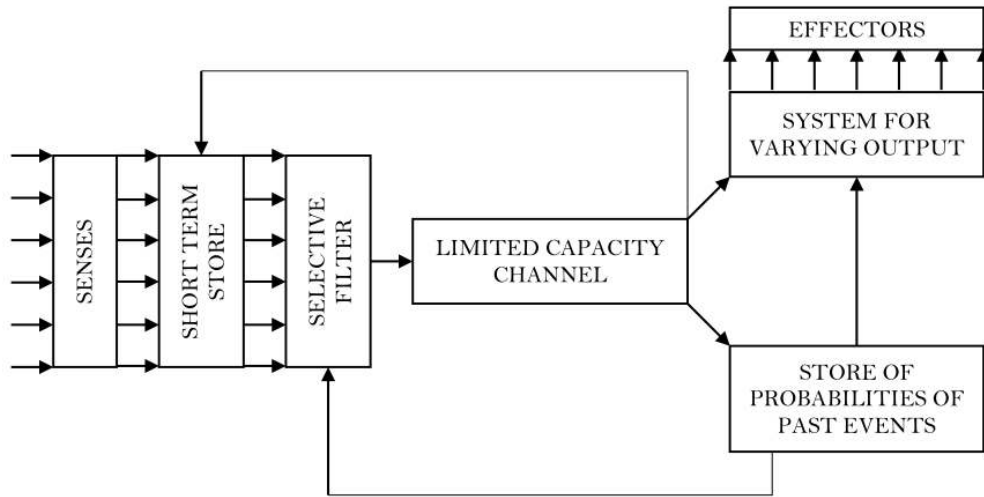


Figure 2. The first flow diagram of the mind, inspired by models of serial computing. Adapted from Broadbent (1958, p. 299).

From out of the cognitive revolution, the cognitive sciences were born. Although there was no unified term for the field until the late 1970s, it first established itself as a formal discipline in the early 1960s. Early labels for it included ‘cognitive studies,’ ‘information-processing psychology,’ and ‘cognitive science’ (Miller, 2003). The cognitive revolution led to several other subdisciplines, as well, including cognitive psychology, computational linguistics, and AI (subdisciplines such as cognitive anthropology came later). Six core disciplines were defined as constituting the cognitive sciences: philosophy, linguistics, anthropology, neuroscience, computer science, and psychology (Sloan Foundation, 1978).

The cognitive revolution had some of the characteristics that Thomas Kuhn identified as characteristic of revolutionary science (Kuhn, 1962/1996). Kuhn’s model is ultimately too linear and teleological to account for the dynamic complexities of the actual history of psychology, cognitive science, and neuroscience. Nevertheless, it provides a useful starting point. Kuhn’s

model predicts that behaviorism would accumulate a mounting series of inconsistencies or anomalies until it reached a crisis that put it in generalized doubt. At this point, multiple competing theoretical paradigms would arise to vie for dominance and ultimately replace behaviorism. The historical details differ in several points from Kuhn's model, but some central elements remain. It was not so much the breakdown of behaviorism as a theoretical paradigm that precipitated the rise of modern computationalism or CRUM. Rather, it was the development of information processing and the computer that allowed for the development of a new model of cognition. It was new technology, rather than a series of mounting anomalies, that led psychology into a crisis. Furthermore, behaviorism was not a monolithic scientific approach in psychology as was Newtonianism. Several other fields of psychology never accepted the behaviorist bracketing of the mind, including the fields of clinical and social psychology (Miller, 2003).

During the crisis period, cybernetics vied for dominance with cognitivism. Cybernetics was an early form of systems theory and flourished from the 1940s to the 1970s, afterwards falling into decline. Its influences were also mathematical and technological, but it took its inspirations from engineering and biology rather than serial computing. It was an early form of antireductionist systems thinking with a focus on feedback mechanisms. In the 1950s, the ecological psychology of James J. Gibson also began to develop as an alternative. Like cybernetics, it was antireductionist but was influenced less by problems in engineering and biology than by Gestalt psychology and problems of perception-action. Cognitivist approaches were the only theoretical paradigm to directly challenge the behaviorist orthodoxy (e.g. Chomsky, 1959). Behaviorism as a theoretical paradigm began to lose institutional legitimacy as

these competing theoretical paradigms demonstrated a new, rigorous science of the mind.⁴

Cognitivism ultimately became the major successor of behaviorism, although (contra Kuhn) the other two major theoretical paradigms did not simply die out. Cybernetics flourished into the 1980s (e.g. Bateson, 1987) and continues to inspire autopoietic theories of life and cognition (see Maturana & Varela, 1980). Ecological psychology is still vigorous to this day and furthermore has inspired novel approaches such as RECS and RECN. Rather than “losing” in a teleological struggle with behaviorism, it has coexisted in parallel with the developments of computationalist science.

Over sixty years since its inception, the cognitive revolution is itself in revolt.⁵ Since the 1980s, a proliferation of new approaches to cognition has sprung up, including connectionism⁶, embodied cognition, dynamical systems-inspired approaches, extended cognition, distributed cognition, enactivism, RECS, and RECN. In the 1970s, work in semantic maps began to challenge the computational, serial processing metaphor of cognition. Nevertheless, this work was fraught with difficulties, not the least being its unfalsifiability. In the 1980s, inspired by semantic maps but invigorated with the rigor of mathematics, connectionism arose as the first significant contender to computationalism. Later in the decade, embodied robotics began to emerge in the laboratory of Rodney Brooks. In the 1990s, a flurry of new approaches emerged,

⁴ Behavioral analysis did not die out, however. In many cases, studies make little meaningful distinction between cognition and behavior (Favela & Martin, 2016). As Kuhn (1962/1996) notes, elements of the old paradigm are sometimes incorporated into the new one.

⁵ I owe the idea that the cognitive sciences are revolutionary in the Kuhnian sense of the term to Dr. Luis H. Favela.

⁶ In some cases, CRUM has transformed itself to adapt to the new approaches. For example, it has been implemented on connectionist architecture (Fodor & Pylyshyn, 1988) and has coopted the problem of perception (Thagard, 2005).

including dynamical systems, extended cognition, and distributed cognition. In the late 20th and early 21st centuries, a new wave of approaches integrating dynamical systems theory, the enactive stance in biology, ecological psychology, and phenomenology began to burgeon (Protevi, 2010). Among them are enactivism, RECS, and RECN.

While connections exist among several of them, many of these competing paradigms are mutually incompatible. This proliferation is the hallmark of the revolutionary phase of a science (Kuhn, 1962/1996). As with cognitivism and cybernetics, they have been influenced by emerging computer technologies and mathematics. Connectionism took its model from the new parallel computing architectures of the 1980s. Dynamical systems approaches, such as RECS and RECN, were inspired by the mature development of complexity theory and nonlinear dynamics in the 1990s. These many different schools of thought are today vying with the established cognitivism for dominance. Today, we are in the middle of a scientific revolution.

1.3 The Computational-Representational Understanding of Mind (CRUM)

CRUM is the main theoretical lens of the cognitive revolution in linguistics, philosophy, psychology, neuroscience, and the cognitive sciences. It is furthermore the dominant conceptual paradigm in studies of social cognition (Gilbert, 1999). For CRUM, cognition is a series of computations that are performed on mental representations (Thagard, 2005). These computations are analogous to computer algorithms implemented in a serial processing architecture. The *human* mind is its prototypical case. Cognition is considered to be exclusively the domain of higher-level mental or neural functions. These functions include language, thinking, knowing, believing, judging, and planning, among others. Different functions are often conceived of as

being processed by different mental modules. Its use of the term ‘cognition’ is conservative and preserves its Latin root meaning of “knowledge.” Affective functions and functions of perception-action are generally not considered to be cognitive phenomena. They are lower functions that cognition may operate with and command. CRUM is implemented in an individual’s neural architecture, either being the brain alone or the wider nervous system. Its borders are in the head or, at furthest, spread throughout the body.

CRUM is not a unitary theory of cognition. Rather, it is a family of related approaches that share the core computational-representational belief and the core analogical inspiration of the serial computer. The approaches themselves are based in logic, rules, concepts, analogies, and images (Thagard, 2005). Logic refers to using systems of formal logic to model the mind or its various cognitive functions—although this approach currently has little support among psychologists. Rule-based approaches are far more flexible than those based in formal logic. They are one of the oldest approaches in the cognitive sciences and began with Simon and Newell’s Logic Theorist in 1959. Concept-based approaches began with semantic maps in the 1970s and are focused on clusters of meanings. Analogy-based approaches understand cognition to be fundamentally analogical, applying known cases to novel analogs. Image-based approaches focus on the otherwise neglected area of visual perception.

1.4 Beyond the Computational Framework: 4EA Approaches to Cognition

The first significant challenge to CRUM was the parallel computing model of connectionism. Since the 1990s, the newer cluster of approaches challenging the dominance of

CRUM can be broadly referred to as 4EA⁷ cognition (embodied-embedded-extended-enactive-affective). These include approaches as diverse as embodied cognition, RECS, RECN, enactivism, distributed cognition, and extended cognition, among others. Like CRUM, they are a family of related approaches rather than a single, unified theory. Unlike CRUM, however, they do not share any single core beliefs or analogical models. Rather, they share a set of practices, including dynamical systems theory, the enactive stance, ecological psychology, and phenomenology (Protevi, 2010). Their stance is nonreductive and is a form of systems theory. Notions of self-organization and emergence replace reductionism. In this respect, they are the heirs of the lost field of cybernetics.

Enactivism serves as an illustrative example of the vast conceptual differences between CRUM and 4EA approaches. Enactivism is a twofold approach viewing perception as continuous with action, which via its recurrent patterns, founds cognition as an emergent organization (Varela, Thompson, & Rosch, 1993, p. 173). In Protevi's (2010) criteria for 4EA approaches, its primary practices are phenomenology and the enactive stance. For many enactivists, the human mind is a complex case of cognition, but minimally cognitive systems also abound in nature. A minimally cognitive system is the least complex system to which one could ascribe cognition in accordance with the deep continuity hypothesis. The deep continuity hypothesis of life and mind states that "[m]ind is life-like and life is mind-like" (Thompson, 2007, p. 128). By this conception of life and mind, bacteria are minimally cognitive systems

⁷ 4E is the more common term. 4EA, or 4E + Affective, also acknowledges Deleuzian approaches (see Protevi, 2006, 2010).

(Maturana & Varela, 1980; Varela et al., 1993). Ticks are another example of minimally cognitive systems, acting only upon perceiving butyric acid (Uexküll, 2010).

An enactive understanding of cognition includes phenomena such as perception-action and basic self-organized modes of organismic organization. The rudiments of mind are found in the organization of bacteria, which is different from their structure. Organization is a self-organized, metastable process that persists across the material changes of structure. Structure refers to the material composition of a system and can vary over time (Maturana & Varela, 1980). It is self-producing, or “autopoietic.” For example, an alveolar cell will continue its basic functions even as tar from tobacco smoke begins to change its chemical makeup (its structure). Its functioning will incorporate the new chemical changes with only slight modifications of its organization, until a threshold is passed and the cell’s organization begins to fail. According to enactivists like Thompson and Varela, such processes are forms of primitive cognition. Higher cognitive functions are different in form, but not different in kind, from such primitive cases. Humans, for example, are larger autopoietic systems consisting of a hierarchy of autopoietic subsystems like lungs or alveolar cells.

For CRUM, the notion that a bacterium, a tick, or an alveolar cell could be cognitive systems is patently absurd. The deep continuity hypothesis is, for CRUM, equally absurd. Rather than cognition being a continuity of processes of varying complexity, it is an entirely novel structure forming by a saltation. This saltatory conception of cognition leaves a significant burden of explanation as to why humans are cognitive.

The work in this paper is broadly 4EA in approach. It is a form of nonreductive systems theory and is informed by dynamical systems theory, the enactive stance, and ecological

psychology. Dynamical systems theory provides the mathematical tools used to model the empirical studies here considered. The enactive stance is taken to view social systems as unified modes of cognitive organization. Ecological psychology informs the basic understanding of perception-action throughout. It does not incorporate phenomenology, as it seeks to understand an exteriority of relations (such as a swarm of ants in frenetic motion) rather than discover an interiority of depths “within” the mind (cf. Deleuze & Guattari, 1987). This paper uses 4EA approaches to present counterevidence to CRUM, although no final judgment is made on the viability of the latter.

1.5 A Method for the Discovery of the Upper Bounds of Cognition

In order to discover the outer limits of cognition, it is first necessary to develop a taxonomy of nonreductive social cognition (Neemeh & Favela, forthcoming). Distributed cognition is one of the few nonreductive concepts of social cognition extant. Nevertheless, it is rooted in case studies of technical-scientific human social systems, including a navy ship, an airplane cockpit, and the HST. This specificity makes it inapt to describe many social systems in nature, whether animal or human. Many types of social phenomena may be cognitive, yet lack any formal framework for recognizing them as such. The development of a taxonomy of nonreductive social cognition, incorporating a wide range of social organizations in nature and human societies, will allow for the expansion of the borders of the “cognitive.” Likewise, it will allow for a clear recognition of the outer limits of cognition. In the following chapter, distributed cognition is described and given a set of formal criteria consistent with Hutchins (1995a; 1995b), Giere (2006), and Kirsh (2006). Next, two additional concepts of nonreductive social cognition

are developed. An exploratory taxonomy of three different types of nonreductive social cognition is thus established. This list is intended to be a programmatic contribution opening the way for further research, not an exhaustive classificatory system. It is then used to explore a variety of social systems across human and nonhuman populations. Few of these cases have previously been considered as cognitive systems, primarily due to a lack of a diversity of concepts of social cognition.

CHAPTER 2: A TAXONOMY OF SOCIAL COGNITION

2.1 Collective Biological and Human Social Systems as Cognitive Systems

Collective biological systems are social groupings of nonhuman organisms such as bird flocks, eusocial insect swarms, wolf packs, and schools of fish.⁸ Human social systems such as small groups, crowds, and societies are distinguished from them primarily by the added complexities of language and culture. This distinction is functional rather than absolute, as other species (particularly nonhuman primates) may express the rudiments of culture, such as social learning (Whiten, 2017), tool use (Mosley & Haslam, 2016), symbolic communication (Gupta & Sinha, 2016), and behaviors specific to local groups of a species (Sapolsky, 2006). However, there is traditionally a wide gulf between these systems insofar as they are objects of scientific investigation. Collective biological systems are traditionally objects in the domain of zoology, ethology, genetics, and other biological disciplines. Human social systems are typically objects of the social sciences, including sociology, anthropology, and social psychology. Sociobiology, evolutionary psychology, and biological or physical anthropology are some of the few instances in which a biological approach to human social systems is taken. Purely cultural and historical approaches have been criticized as being biologically naive (Pinker, 2003) or outright dismissive (Marsland & Leoussi, 1996).

A cognitive understanding of collective biological and human social phenomena cuts across disciplinary boundaries and trite nature/nurture controversies. Couzin (2008) first

⁸ The discussion of nonhuman organisms must be very careful to avoid any anthropomorphic ascriptions of mental states, feelings, beliefs, and desires.

suggested that collective biological systems are cognitive systems. Some human social systems, such as a navy ship, an airplane cockpit, and the HST, have been defined as cognitive systems (Hutchins, 1995a, 1995b; Giere, 2006). As cognitive systems, they may be expressive of genetic, ethological, sociological, historical, chemical, and cultural properties without being exclusively defined by any single one.

Both collective biological and human social systems are cognitive systems.⁹ There is no universally-accepted definition of ‘cognition’ with which to substantiate this claim, however. The multiple theoretical paradigms of cognition operating in the cognitive sciences are often mutually incompatible. In an attempt to bridge the gap, Theiner and O’Connor introduce a “big tent” approach that attempts to capture the common properties of cognition in these various theoretical paradigms. Their big tent lists the common properties of cognition presented by competing theories in order to arrive at an ecumenical and minimally-controversial definition of cognition (Theiner & O’Connor, 2010). Unfortunately, their big tent is not as ecumenical as they think and is inconsistent with nonrepresentational approaches (Chemero, 2009; Favela, 2014; Hutto & Myin, 2013; Thompson, 2007). Rather than argue that collective biological and human social systems are cognitive systems in general (as a “big tent” approach might), they are presented as different cases of specific types of cognitive systems.

In the following, an exploratory taxonomy is developed to subsume the variety of cases of social cognition. First, social cognition in CRUM is defined as collective cognition. The terms ‘self-organization’ and ‘emergence’ are then discussed in order to facilitate the presentation of

⁹ “Consciousness” and “cognition” are loosely related terms and are sometimes conflated with one another, but they remain discrete concepts (Davies, 1999). Flocks of birds, for example, are emphatically *not* conscious, although individual birds within the flock are.

the taxonomy of nonreductive social cognition. Three types are identified: distributed cognition, swarm intelligence, and superorganismic cognition. This list is not presented as exhaustive and other, yet-to-be-discovered types may exist. Furthermore, they are not presented as absolute categories and there may be significant slippage across them.

2.2 Social Cognition in CRUM: Collective Cognition

Social cognition in CRUM is “collective cognition.” Collective cognition is a reductionist understanding of social cognition in which the cognitive properties of the whole are reducible to the causal interactions of the cognitions of its agentic parts (Giere, 2006). Groups are only cognitive insofar as its members are cognitive. For CRUM, cognition begins and ends with the individual. Any social grouping therefore cannot be characterized as cognitive other than by noting that its members are such. Collective cognition is compatible with and comparable to methodological individualism in economics and sociology, which understands individuals as the basic, atomic unit of analysis in society (Hayek, 2010). That is, the group is nothing more than an epiphenomenon of the interactions of its individual members. Thus, to say that a wolf pack is a collective cognitive system is simply to note that individual wolves are cognitive systems and that they interact with one another.

Collective cognition, like methodological individualism, is not necessarily “computational” in the standard sense of algorithms and serial processing. Dynamical systems models of methodological individualism have been developed (Sawyer, 2005) and some CRUM approaches are tentatively opening up to this kind of modeling (Thagard, 2005). In these cases,

any emergent properties are considered to be simply effects of our current ignorance (referred to below as “epistemological emergence”).

2.3 A Note on Meaning of ‘Self-Organization’ and ‘Emergence’

In order to introduce the taxonomy of nonreductive social cognition, it is first necessary to discuss the otherwise ambiguous terms ‘self-organization’ and ‘emergence.’ Self-organization is a situation in which a system’s organization is established by its very own functioning. That is, its organization is not heteropoietic. A heteropoietic system (or “machine” in Maturana and Varela’s parlance) is organized or controlled by an extraneous process. When heteropoiesis is defined as “occur[ring] in the space of human design,” a common feature of human-produced machines is captured: that of heteronomous control (Maturana & Varela, 1980). They are “activated, steered, and controlled from the outside” (“Heteropoietic,” 2004). For example, a mechanical clock is a heteropoietic system. Its purpose—to keep time—is imposed upon it by its human creators and users. Its organization is designed and maintained by the clockmaker rather than arising from the inner workings of the clock itself. If its gears begin to malfunction, then an expert must repair it.

Self-organization arises simultaneously from the inner, local workings of a system and from its global behavior. There is no overarching plan or purposive organization imposed upon a self-organized system. Often they are seen in nonlinear dynamical systems (Depew & Weber, 1999). They express “spontaneous patterning and order” (Riley & Holden, 2012, p. 595). Rayleigh-Bénard convection cells are a paradigm case of self-organization. As the lower-temperature top surface is heated by the higher-temperature bottom surface, a spontaneous order

arises observable as a series of adjacent cells (Prigogine & Stengers, 1984). These cells and the dynamical convective flows sustaining them are created by the local interactions of molecules being heated (see Figure 3). There is no plan, intentional order, or computational controller organizing these convection cells. They are nothing like the gears of a mechanical clock, which are calculating mechanisms created by an engineer for the specific purpose of keeping time. To identify a cognitive system as self-organizing is to say that it is not organized by a controller like a self, a homunculus, or any such “ghost in the machine”. Computational and homuncular accounts of cognition, such as the concept of collective cognition, are therefore not self-organized.

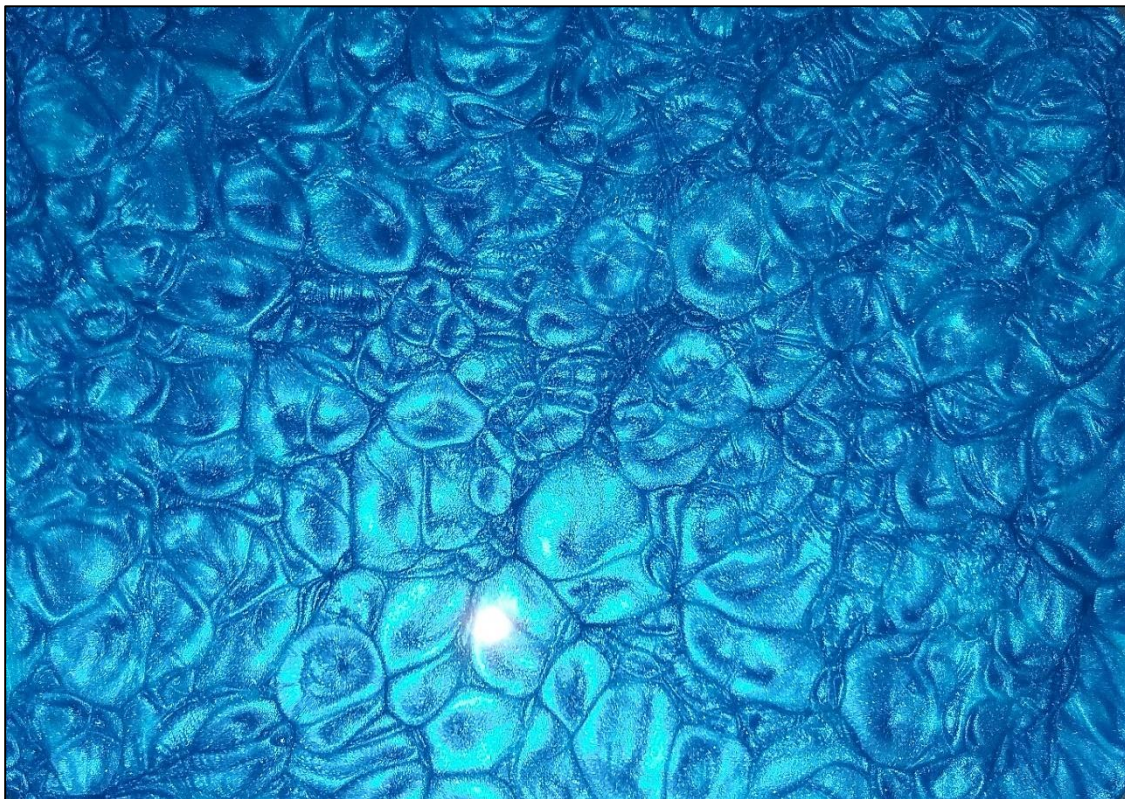


Figure 3. Rayleigh-Bénard convection currents as seen from the surface. Blue mica suspended in oil.
Author photo.

Emergence is a far more nuanced concept. Within complexity science, self-organized systems are usually identified as emergent, but these are discrete concepts. I will focus on three principle types of emergence: epistemological emergence, weak ontological emergence, and strong ontological emergence (cf. Theiner & O'Connor, 2010). Emergence entails a causal and ontological autonomy from the lower-level entities or processes a system depends upon (Wilson, 2015). It is entirely possible that this “autonomy” can be specious and merely an effect of an investigator’s ignorance. The proverbial case of such specious autonomy is water, whose properties were once thought to emerge from H₂O molecules (Stengers, 2011). It is now known that the properties of water can be fully understood reductively in terms of the properties of hydrogen and oxygen atoms alone. This is a case of epistemological emergence, which includes any “emergent” property that does not entail a denial of reductionist explanation.

Ontological emergence can be weak or strong (cf. Wilson, 2015). Weak ontological emergence entails a non-reductive physicalism. Strong ontological emergence is inconsistent with the causal closure of physics (Theiner & O'Connor, 2010). For the purposes of this essay, the differences between these are irrelevant. To identify a cognitive system as emergent is to say that it arises but is causally and ontologically autonomous (whether weakly or strongly) from the lower-level processes constituting it (e.g. the nervous system or the individual birds of a flock). A system that is both self-organized and emergent organizes at the local level and gives rise to a global level that in turn has a reciprocal causal efficacy over the local.

2.4 Distributed Cognition

Edwin Hutchins introduced distributed cognition as an alternative understanding of

cognition in collective systems. Distributed cognition emerges as a property at the system level. Paradigm cases include a navy ship, an airplane cockpit, and the HST (Hutchins, 1995a, 1995b; Giere, 2006). A network of agents and tools working continuously and in tandem towards a collective goal constitutes distributed cognition. It differs from extended cognition in that it is disbursed over a network of multiple agents and nonagentic tools, whereas a single agent and nonagentic tools paradigmatically constitute extended cognition. Furthermore, in a distributed cognitive system, no single agent or nonagentic tool has a complete survey of the entire system.

Amon and Favela provide a useful set of criteria for distributed cognitive systems. However, their understanding of distributed cognition differs from that of Hutchins, as they seek to distinguish extended from distributed cognition. While this is admittedly something that remains confused in the literature (see Kirsh, 2006), it is not a relevant distinction here. The following is a modified list of their criteria of distributed cognition (Amon & Favela, 2017) consistent with the usages of Hutchins (1995a, 1995b), Giere (2006), and Kirsh (2006). *S* is a distributed cognitive system if:

- D1. *S* is emergent or exhibits emergent behavior.
- D2. There is a continuous coordination of agents and nonagentic tools as members of *S*.
- D3. Each agent maintains a degree of individual agency within *S*.
- D4. Each agent actively participates in the overall goal or joint task in which *S* is engaged.
- D5. There is a specialization of functions among the members of *S*.
- D6. The cognitive behavior of *S* is complex and not limited to perception and

locomotion.

Distributed cognition is not a property of the system itself (Giere, 2006). It is a property of individuals composing the system and is preserved insofar as they constitute that system. Individual agency is not significantly diminished or lost when individuals constitute a distributed cognitive system. For example, the captain of a ship is still a fully-fledged individual and only enacts the role of captain insofar as they desire to (the captain can derelict their duties or even sabotage the mission). Agents in these cases are in themselves complex cognitive systems. Note that, although it may be emergent, distributed cognition is not necessarily self-organized. The HST, for example, is a straightforward example of a heteropoietic (other-organized) machine. The engineers, scientists, technicians, and astronauts that designed and operate it determine its organization. It is not produced and maintained by its own internal processes and functions.

Distributed cognition requires individuals with strong agency and complex individual cognition in order to be constituted. For example, the HST is not simply an orbital telescope generating images of remote celestial objects. As a technical-scientific institution, it produces falsifiable scientific claims (e.g. about the age of the universe). However, many organisms, such as ants and fish, are minimally cognitive and agentic (if at all). Although some have considered such systems as cases of distributed cognition (e.g. O'Donnell et al., 2015), they do not have the requisite agency or cognitive complexity to be true cases of distributed cognition. Two more fitting ways to think of such systems are in terms of swarm intelligence and superorganisms.

2.5 Swarm Intelligence

Swarm intelligence is a concept born in computing and is not a concept of cognition. It is

a form of biologically inspired computing in which algorithms are abstracted from swarming organisms such as bees, ants, wolves, and other collectivist organisms (Beekman, Sword, & Simpson, 2008). These algorithms describe emergent and self-organizing phenomena (Yang & Karamanoglu, 2013). This terminology is appropriated to describe simple, self-organizing, emergent cognitive systems capable only of rudimentary behavior and having a roughly isomorphic organizational structure¹⁰. A system *S* is swarm-intelligent if:

- SI1. *S* is self-organizing and emergent.
- SI2. There is a continuous coordination of individuals as members of *S*.
- SI3. Individual agency is minimal insofar as the individual constitutes *S*.
- SI4. The cognitive behavior of *S* is limited to perception and locomotion.¹¹
- SI5. Communication or interaction between members of *S* is minimal and there is no communication of intentions.
- SI6. The organization of *S* is relatively isomorphic. There is no specialization of functions between members of *S*.

Swarm intelligence entails a minimal level of agency on the part of the system's individual members. This does not mean that the individuals qua individuals are necessarily minimally agentic, although they may be. Rather, individuals insofar as they constitute the collective cognitive system are minimally agentic. A person caught up in a stampede serves as a prime example of an agent that nevertheless may be transiently and contextually minimally

¹⁰ By this I mean not that the organizational pattern is uniform, but that the organizing principles are. There is no specialization and all organisms qua members of the system perform the same function.

¹¹ This can also be conceived of as a single loop of perception-action (Gibson, 1979/2015).

agentic. The person has a complex set of personality traits, beliefs, desires, memories, ideas, and linguistic capabilities. Nevertheless, within a large, energetic crowd, their behaviors may be limited to a very circumscribed set of perceptions and movements. Few of the complexities of language and communication may persist in such a crowded and noisy situation. For the individual to run in a certain direction, it suffices that the crowd is collectively running in that direction. The individual may or may not even know specifically from what they are running from or towards.

2.6 Superorganismic Cognition

Some minimally agentic systems may not be limited to simple movement, however. Superorganisms are capable of comparatively complex behavior. Two different concepts are extant in the literature: medical and sociobiological. The medical concept of the superorganism sees the human as a network of organisms, from the human itself to its microbiome, parasites, and foreign DNA (Kramer & Bressan, 2015). The sociobiological concept of the superorganism describes the evolutionary and organizational properties of eusocial insect colonies. This terminology is appropriated here to describe complex, self-organizing, emergent cognitive systems capable of moderately complex behavior and having an anisomorphic organizational structure. A system S is superorganismic if:

- SO1. S is self-organizing and emergent.
- SO2. There is a continuous coordination of individuals as members of S .
- SO3. Individual agency is not preserved insofar as the individual constitutes a member of S .

- SO4. Each individual actively participates in the joint tasks in which *S* is engaged, although these tasks may be atelic.
- SO5. The cognitive behavior of *S* is moderately complex and is able to perform more than perceptual and locomotive functions.
- SO6. Communication between members of *S* is moderately varied and complex, but there is no communication of intentions.
- SO7. The organization of *S* is complex; there is a specialization of functions among members of *S*.

Superorganismic cognitive systems entail a collective participation in a joint task.

However, unlike with distributed cognition, this joint task may not be purposive or intentional.

For example, the sailors of a ship are self-aware of a common goal, even if that goal varies slightly from person to person: navigate to point *A*. Ants, however, have no such comparable self-awareness when they are constructing an anthill or are converging upon a food source. Nevertheless, they perform the tasks conjointly and in accordance with a differentiation of function.

In the following, seven case studies are evaluated as cases of collective, distributed, swarm-intelligent, or superorganismic cognition. They are divided into two series: collective biological systems (four cases) and human social systems (three cases). As previously noted, this division is purely practical and is not necessarily intended to reflect any essential differences in the phenomena studied. For each case, the evidence is presented and then evaluated according to the taxonomic criteria of nonreductive social cognition.

CHAPTER 3: CASE STUDIES OF COLLECTIVE BIOLOGICAL SYSTEMS

3.1 Collective Biological Systems

The idea of a collective mind—and, indeed, the term ‘superorganism’ itself—dates back to the sociology and psychology of the 19th century (Theiner & O'Connor, 2010). Until recently, it was not possible to study the properties of collective systems like flocks of birds by analyzing the individual movements of its members. In 1995, Tamás Vicsek developed the first model capable of realistically modeling swarming behavior. This has become known as the Vicsek model and is the standard by which other models of swarming behavior are compared. Such models are based in statistical mechanics and are known as self-propelled particle (SPP) models. New advances in computer and video technology have also made it possible to record data on the kinematics of organisms within groups (Couzin, 2008), for example, the movement and vectors of individual pigeons in a flock (Kattas, Xu, & Small, 2012). The following studies are of bird flocks, eusocial insect swarms, wolf packs, and schools of fish. Each case is analyzed for evidence of being a specific type of cognitive system (distributed cognition, swarm intelligence, or superorganismic cognition) according to the previously established criteria.

3.2 Bird Flocks

3.2.1 Evidence. Flocks of birds are among some of the most profoundly enigmatic and beautiful phenomena in biology. A murmuration of starlings, for example, is a massive,

sinuously twisting, whirling, and chaotically evolving flock that acts as a unit. It can evade predators like falcons, find food and water, and navigate to roosts. Already this suggests flocks may be a minimally cognitive system with complex locomotive and perceptual faculties. It can evade predators (perception of danger + evasion), it can locate food and water (perception of resources + goal-like movement), it can navigate to roosts (memory + goal-like movement), and it can migrate.

SPP models and empirical vector analyses of individual birds in flocks show that the global behavior of flocks can arise from the local interactions of individual birds. Starling (*Sturnus vulgaris*) flocks can be realistically modeled by aligning neighboring birds to one another. A single bird maintains a set of proximal birds with which to keep aligned. Such local interactions result in an emergent directionality for the flock as a whole (Bialek et al., 2012). There is a limit to how many birds a given bird can align with. In simulations, if a bird is set to align with too many neighboring birds, the entropy of the system destabilizes it and breaks apart the flock into several smaller groupings (Castellana, Bialek, Cavagna, & Giardina, 2016). Individual birds coordinate their movement with a small number of neighboring birds (Bialek et al., 2012). Similar results have been obtained studying the flight vectors of homing pigeons (*Columba livia domestica*; Kattas et al., 2012).

SPP models are still in their infancy, as are computerized vector analyses of individual bird flight data in a flock. Nevertheless, it is clear at this point that flocks emerge from the limited interactions of individual birds rather than more widespread, even flock-wide, interactions. That is, unless other strong, cohesive social forces as yet unknown exist counteracting the entropy of the system (Castellana et al., 2016).

The cohesiveness and unified directionality of flocks of birds is maintained through a simple system of alignment (Bialek et al., 2012; Couzin, 2008). Couzin and colleagues (2002) analyzed the formation of swarms, flocks, and schools in terms of three basic parameters: attraction, repulsion, and alignment or orientation (see Figure 4). Changes in the values of these parameters creates different aggregate patterns: swarm, torus, dynamic parallel group, and highly parallel group. Flocks exhibit the swarm aggregation type, which is the least efficient medium for the propagation of information, allowing less cohesive and swift of a response to e.g. an oncoming predator (Couzin, Krause, James, Ruxton, & Franks, 2002). Nevertheless, it is effective enough to allow starlings, for example, to successfully evade a predating hawk.

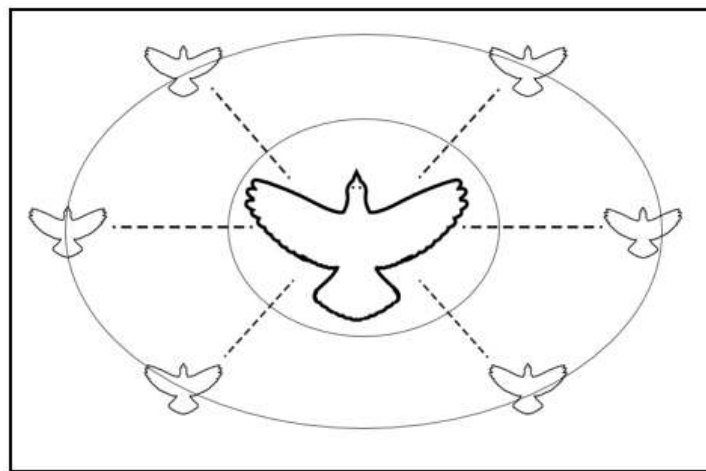


Figure 4. Individual birds within a flock coordinate their movements relative to the positions of a small number of proximal birds. The outer circle represents the zone of attraction, the inner circle the zone of repulsion, and the space in between them. From Neemeh and Favela (forthcoming).

The directionality of the flock is an emergent property of local interactions of individual birds. The local interactions of birds serve as the foundation for the long-range spatial correlations and behavior of the flock (Cavagna, Giardina, & Ginelli, 2013). One local group may begin to change direction as the individuals notice a hawk in the distance. As they begin to

shift, their neighbors likewise shift, causing a chain reaction propagating throughout the entire flock as a wave (Couzin, 2008). The flock then moves away from the hawk, although only a few individuals in one locale may have actually seen it or “know” why they are shifting directions. The overall directionality of the flock is continuously punctuated by smaller perturbations and shifts in direction. This gives flocks their wisp-of-smoke-like appearance and is due to their imperfect, noisy alignments (Cavagna, Duarte Queirós, Giardina, Stefanini, & Viale, 2013; Chen, 2015). This leads to the continuously shifting movements of the flock as a whole.

3.2.2 Bird flocks as swarm-intelligent systems. Couzin (2008) is one of the sole studies to categorize flocks as cognitive. In the Vicsek and other SPP models of biological systems, flocks are categorized as swarms. While this may be useful for modeling, the behavior of flocks and swarms are fundamentally different. Flocks are capable of far less complex behaviors than are swarms. Similarly, the communication within a flock is highly circumscribed, while a colony of ants has up to 12 different communication modalities (Hölldobler & Wilson, 1990). Flocks are best understood as swarm-intelligent systems.

Flocks are self-organizing and emergent (SI1). The movement and directionality of the flock does not unfold as part of any intentional plan and it is not organized by a controller. It is thus not heteropoietic. It is wholly organized by the local interactions of individual birds. Furthermore, these local interactions give rise to global behavior relatively autonomous from the individual birds themselves. This global behavior in turn is causally affects individual birds.

Individual birds within the flock, qua members of the flock, do not retain any appreciable measure of agency as does the captain of a ship. Although the perception of the hawk is indeed

distributed in only a local area of individual birds, the flock is not a distributed cognitive system. Neither is it a superorganism, however suggestive the sight of a murmuration may be. Rather, flocks are swarm-intelligent cognitive systems. There is a continuous coordination of individuals as members of the flock (SI2). SPP models are inspired by the statistical mechanics of particles, but birds are by no means mere blind particles stochastically bouncing off one another. Individual birds maintain alignment (with a degree of noise) with a small set of proximal birds (Bialek, et al., 2012; Cavagna et al., 2013). Individual birds *actively* coordinate their movements in the flock. The mechanism of this alignment is possibly a simple repulsive effect or an effect created by repulsion, alignment, and attraction (Castellana et al., 2016; Couzin et al., 2002).

Individual agency is minimal insofar as the individual constitutes a part of the flock (SI3). Birds are not free to interpret their tasks, perform other tasks, or even decline to perform a task. The system is too simple to allow for the complexity of agency. The cognitive behavior of the flock is limited to perception and locomotion (SI4). Swarms of yellow meadow ants (*Lasius flavus*), for example, herd and harvest aphids (Ivens, Kronauer, Pen, Weissing, & Boomsma, 2012). Nearly all swarms of ants form physical colonies out of dirt, sand, or stone. Flocks of birds are unable to perform comparably complex behaviors. Nesting is irrelevant as nests are built by individuals, not by flocks as such. The flock is limited to evasion, migration, and food-locating behaviors.

Communication or interaction between members of the flock is minimal and there is no communication of intentions (SI5). There is no direct communication, *per se*. There is no leader squawking orders or warning of impending raptors. Rather, the only interaction is through proximity—repulsion, alignment, and attraction. The organization of the flock is simple and

there is no specialization of functions between its members (SI6). All birds in the flock have the same function within the flock, viz. the same relations of repulsion, alignment, and attraction. Flocks therefore fulfill the criteria SI1-6 and are swarm-intelligent systems.

3.3 Eusocial Insect Swarms

3.3.1 Evidence. Swarms are the paradigm case of superorganisms in the sociobiological sense of the term.¹² The case must be made whether they constitute superorganisms in the cognitive sense of the term I have defined. In the literature, these swarms mostly include eusocial species of Hymenoptera—ants, bees, and wasps—but also termites (of a different order, Blattodea) and some beetles (*Austroplatypus incompertus*).¹³ Ants have a range of degrees of cohesiveness as a collective, from the tiny, loosely-associated colonies of *Temnothorax albipennis* to the sprawling masses of army ants (a name covering a variety of convergently-evolved species) carpeting the forest floors. They are characterized by a caste structure that is formed in the process of sociogenesis (Hölldobler & Wilson, 2009). Individuals express up to twelve distinct types of communication, including alarm, simple attraction, recruitment, grooming, trophallaxis, exchange of food, facilitating or inhibiting a group activity, recognition, caste determination, control of reproducers, territorial signals and nest markers, and sexual

¹² The sociobiological definition of a superorganism is a eusocial colony characterized by 1) a caste system, 2) multigenerational coexistence, and 3) a situation in which non-reproducers care for the young (Hölldobler & Wilson, 2009). Intergroup competition is also fundamental (Reeve & Hölldobler, 2007).

¹³ Non-eusocial insect swarms, such as of mosquitos, are not considered in this section and do not constitute superorganismic cognitive systems.

communication (Hölldobler & Wilson, 1990). This contrasts sharply with flocking birds, which are limited to visual flight alignment.

Ants themselves function according to a series of basic functions. Ant colonies arise precisely from these basic processes governing local ant interactions. Surprisingly complex behaviors on the collective level can arise from these simple, local interactions (Sekara et al., 2015). Particularly striking examples of emergent behavior includes army ants creating shelters out of their bodies and termites building “air-conditioned” nests (Hölldobler & Wilson, 2009). A common example of how such algorithms result in emergent, self-organized behavior is how ants find food sources. Not only are they able to locate food sources, but they are also able to “discern” their relative qualities through the mechanism of positive feedback in pheromone trails (Beekman, Sword, & Simpson, 2008). Such positive feedback loops leading to the incitement to working behavior are known as stigmergic. These pheromone trails effectively create dynamic routes to food sources by incrementally strengthening a strong lead. For example, an ant locates a food source and leaves a pheromone trail. Another ant follows that trail, thereby strengthening it with pheromones. This strengthened pheromone trail attracts even more ants, who further strengthen it. Smaller food sources will run out before a very strong trail is built up, so their trails remain weak. Thus, the colony is able to “discern” the quality of a food source and “send” workers to collect it—the “goal” being ultimately atelic. This stigmergic structure in ant swarms is reminiscent of Hebbian learning (Couzin, 2008).

3.3.2 Eusocial insect swarms as superorganisms. The few extant studies of swarms as cognitive systems have categorized them as cases of distributed cognition (O'Donnell et al.,

2015; Couzin, 2008). In SPP modeling, swarms are categorized along with flocks, schools of fish, and sometimes human crowds as instances of swarming (cf. Moussaid, Garnier, Theraulaz, & Helbing, 2009). Distributed cognition is not useful for understanding swarms because they are markedly different from systems such as the Hubble Space Telescope or a ship. There is little to no agency in constituent members of a swarm, although their behavior is far more complex than that of flocks of birds. Neither are they cases of swarm intelligence, as their complexity is of an order far surpassing flocks. They are best understood as superorganisms.

Swarms are self-organizing and emergent (SO1). The organization of the swarm is maintained through sociogenesis and the local interactions of ants themselves. The sociogenesis of the caste structure arises largely through epigenetics, though the caste forms themselves are genetically coded (Hölldobler & Wilson, 2009). Ant ontogeny is epigenetically determined into one of several castes. Depending upon the species, the number of castes can be two or more (Hölldobler & Wilson, 1990). This contrasts with flocks, where each individual member is functionally equivalent to the next. Individual ants, functionally and ontogenetically specialized into castes, produce the global organization of the nest by their local behaviors. This global organization in turn affects the individual ants causally, e.g. in stigmergy. The queen is not a controller, nor is there any central plan or computational system. Thus, it is self-organizing. Furthermore, swarms are emergent. Individual insects are the substrate upon which the swarm depends upon for existence, but the swarm itself operates autonomously from these individuals.

There is a continuous coordination of individuals as members of the swarm (SO2). This coordination occurs through stigmergy and other modes of communication, such as exciting other ants by brushing with antennae. This coordination allows the swarm to achieve collective

behaviors like defense, resource collection, and nest building. Individual insects are not agentic insofar as they constitute the swarm (SO3). Although intergroup competition exists, the individual is unable, like the captain of a ship, to choose to thwart the swarm or defect. It is doubtful, however, that ants or bees could be said to be agentic to begin with. Each individual actively participates in the joint tasks in which the swarm is engaged (SO4). Every ant in the swarm has a function that it performs. There are no “freeloader ants” or nonfunctional units within the colony.

The cognitive behavior of the swarm is moderately complex and is able to perform more than perceptual and locomotive functions (SO5). Unlike flocks, swarms are capable of gathering food, building nests, and other complex behaviors. Correlatively, communication between members of the swarm is moderately varied and complex, but there is no communication of intentions among the swarming insects (SO6). As noted, ants exhibit up to 12 different types of communication patterns. The organization of the swarm is complex; there is a specialization of functions between members of the swarm (SO7). This is evident in the caste structure of the swarm and contrasts with flocks, whose members are functionally equivalent. Swarms thus fulfill SO1-7 and are best understood to be superorganisms.

3.4 Wolf Packs

3.4.1 Evidence. Wolf packs range from as few as four to as many as 30 members and are generally family units (Mech, Smith, & MacNulty, 2015). These groups are far smaller than anything on the scale of swarms and flocks. Individual wolves are far more cognitively complex

than individual birds or ants. This in itself, however, does not necessarily imply anything about their group dynamics. Birds, as we have seen, certainly have larger cognitive capacities than ants, and yet flocks are less complex than swarms.

Wolves in a pack are markedly different from SPP models of swarming. They move and hunt as individuals, yet they maintain pack formation. That is, individuals converge upon prey and a single wolf ultimately takes it down (Tang, Fong, Yang, & Deb, 2012). The smaller the pack is, the more efficient it is at hunting (Mech et al., 2015). Packs with up to 30 members are far less cohesive and unified in function. In simulations of wolf hunting behavior, the only information individual wolves require to perceive and communicate is other wolves' spatial positions (Muro, Escobedo, Spector, & Coppinger, 2011). This explains why wolves appear to have no explicitly organized hunting strategy (Mech et al., 2015). Their hunting behavior is emergent rather than controlled. Their movement arises out of a few basic rules such as following the prey and simultaneously following the breeder¹⁴ (see Figure 5). The wolves individually have similar goals (e.g., catching the deer), but the behavior of the pack is not telic or intentional. Even apparent hunting strategies such as encircling, ambushing, and relay hunting are explicable in terms of basic rules creating emergent patterns (Muro et al., 2011).

During the hunt, wolf packs exhibit some level of coordinated behavior even though they maintain strong individual agency. They do not consistently employ coordinative techniques (Mech et al., 2015). In some situations, however, it appears that wolves communicate intentions such as waiting in ambush (Mech, 2007). Nevertheless, the typical hunting patterns of encircling, ambushing, and relay hunting do not necessarily require planning or explicit control to enact.

¹⁴ A breeder (“alpha” in older literature) is an older, dominant wolf (Mech et al., 2015).

These hunting patterns can emerge from the local interactions of individual wolves (Tang et al., 2012). Encircling, for example, emerges from two simple procedures of interaction: move towards prey and away from other encircling wolves (Muro et al., 2011).

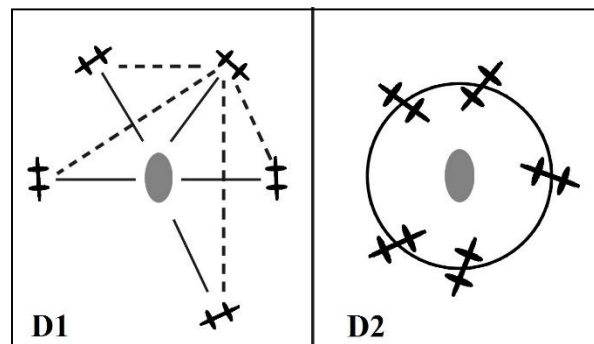


Figure 5. D1. Individual wolves continuously coordinate their movements based on the spatial positions of the breeder (top right) and prey (center). D2. This can result in emergent hunting patterns, such as encirclement. From Neemeh and Favela (forthcoming).

3.4.2 Wolf packs as distributed cognitive systems. Wolf packs are best understood as distributed cognitive systems. Packs are self-organizing collectives, although this is not a necessary condition for D1. A breeder may loosely help serve as a focal point for the pack, but there is no command structure or central controller within the pack itself. The breeder is neither a guide nor a leader. Although Mech (2007) notes that wolves have a degree of mutual understanding of one another's behaviors and intentions, they do not communicate complicated hunting strategies. The typical hunting patterns of encircling, ambush, and relay hunting arise out of simple rules of local interaction among the wolves and their quarry. The organization, coordination, and hunting patterns of wolf packs are emergent (D1).

There is a continuous coordination of wolves as members of the pack (D2). This coordination is primarily visual and is based on spatial information. Wolves coordinate their movements among themselves by reference to the spatial positions of breeders and the prey. This

continuous and dynamic spatial coordination leads to the emergent hunting patterns sometimes observed. Each wolf maintains a degree of individual agency within the pack (D3). Wolves are not tightly bound to their behavior as are ants. Wolves are only loosely associated within the pack and they take many individual initiatives while hunting (cutting off an animal, for example).

Each wolf actively participates in the overall goal or joint task in which the pack is engaged (D4). Even very young and incapable wolves participate, less to actually catch prey than to learn how to hunt. Breeders tend to make the kill, while other wolves focus on wearing out prey (Mech et al., 2015). There is a specialization of functions among the members of the pack. Packs are hierarchical and this hierarchy determines the functional specialization of its members. Along with the prey, the breeder serves as a reference point for the spatial coordination of other wolves (Tang et al., 2012). The breeder's role as a coordinating reference is stable throughout time and is not a transient position. The cognitive behavior of the pack is complex and not limited to basic perception and locomotion (D6). Hunting is a goal-oriented process of food gathering. This food gathering is a collective effort, for while a single wolf usually makes the kill, the pack devours it collectively. Flocks of birds, in contrast, are limited to movement. Packs thus fulfill the criteria D1-6 and are distributed cognitive systems. In itself, this is a remarkable finding. It implies that there are some organizational similarities between some human technical-scientific systems and wolf packs.

3.5 Schools of Fish

3.5.1 Evidence. Schools of fish vary widely in size, density, composition, and structure. Schools of fish are not always exclusively composed of a single species and some contain several species. This is particularly interesting because it potentially points to more than a mere genetic determination of schooling behavior and structure.

Couzin and colleagues (2002) abstract swarming behavior into four basic patterns: swarm, torus, dynamic parallel group, and highly parallel group. Viscido and colleagues (2002) note even more differences among schools. “Swarming,” according to their criteria, entails basic processes of attraction and repulsion without any process of orientation. Members of the group do not seek to align themselves with one another, but they do seek to both avoid getting too close and too far away from neighbors. Some types of schools exhibit this type of minimal structure (Pitcher & Parrish, 1993). The toroidal formation, or what Moussaid and colleagues (2009) refer to as vortices or mills, is characteristic of some species such as barracuda. Most schools, however, are generally characterized by either the dynamic parallel group or the highly parallel group. In other words, they operate through processes of attraction, repulsion, and alignment (Couzin et al., 2002).

These patterns are themselves dynamic and schools of fish may transition between any number of them. Such transitions (e.g. from a dynamic parallel group to a torus) occur in response to environmental changes such as an oncoming predator (Couzin et al., 2002; Moussaid et al., 2009). As with bird flocks, not all of the constituent members of the school perceive the oncoming predator (Moussaid et al., 2009). This would be particularly impossible in schools

upwards of a million fish. Nevertheless, the school *as a unit* works to avoid the predator. While birds in a flock maintain the processes of attraction, repulsion, and alignment visually, fish use two parallel systems. Alongside their visual system, fish have an organ known as the lateral line system. It is sensitive to changes in water flow and directionality, ultimately informing the fish about the movements of its neighbors (Moussaid et al., 2009).

3.5.2 Schools of fish as swarm-intelligent cognitive systems. Schools of fish are best understood as instances of swarm intelligence. In fact, they bear many organizational similarities to bird flocks. They are both self-organizing and emergent collective organization (SI1; Parrish & Viscido, 2002). There is no external, heteropoietic control mechanism such as a leader or group of leaders (Moussaid et al., 2009). As with bird flocks, the overall organization results from the local interactions of attraction, repulsion, and alignment. There may be more variations in the patterns that schools can assume, however. Parrish and Viscido (2002) identify upwards of nine. These processes are continuous and the school is perpetually in motion so long as it maintains its unity and identity. There is thus a continuous coordination of individual fish as members of the school (SI2).

Individual agency is minimal insofar as the individual fish constitutes the school (SI3). For example, scientists and engineers working on the HST have the capacity to relinquish their duties, perform them incorrectly, or neglect to perform them altogether. Fish have no comparable capacity to “rebel” against the school. Their behavior within the school is largely deterministic in the sense that they will perform the processes of attraction, repulsion, and alignment unless rendered incapable of doing so by illness or accident.

The cognitive behavior of the school is limited to perception and locomotion (SI4). Individual fish have more complex abilities, such as feeding or producing offspring. However, insofar as the fish constitutes the school, it is limited to the three basic processes of alignment. Its further capacities are not preserved within the school. The fish does not lose its capacities; rather, it only performs them qua individual (or, at best, a small group). Communication or interaction between members of the school is minimal and there is no communication of intentions (SI5). The communication of spatial position and directionality is achieved through the visual and lateral line systems. The shifts in direction (e.g. in response to a predator) or the shifts in pattern are not planned out or dynamically communicated. They emerge from the local alignment interactions of the fish themselves.

Finally, the organization of the school is relatively isomorphic. There is no specialization of functions between its members (SI6). The only functionally distinguishing features among different fish of the school are relative speeds. Faster fish tend to be at the front of the school, while slower fish tend to be towards its end (Moussaid et al., 2009). This does not imply any hierarchy of control, however. Overall, schools of fish satisfy SI1-6 and are best understood as swarm-intelligent cognitive systems.

CHAPTER 4: CASE STUDIES OF HUMAN SOCIAL SYSTEMS

4.1 Human Social Systems

Human social systems have been studied far longer than their nonhuman counterparts. Aristotle (1995) first studied the society as a unit nearly two-and-a-half millennia ago. The scientific study of these systems primarily takes place within the disciplinary confines of sociology, anthropology, social psychology, and economics. Certain types of technical-scientific systems were first studied as cognitive systems by Edwin Hutchins in the mid-1990s. Hutchins developed the concept of distributed cognition to explain the behavior of a navy ship (1995a) and an airplane cockpit (1995b). Giere (2006) later applied this concept to understand the working of the Hubble Space Telescope (HST). In these studies, both human agents and nonagentic tools such as speed bugs (a type of airspeed indicator) are considered as a unified cognitive system (Giere & Moffatt, 2003). The present study does not dispute the categorization of these systems as distributed cognition, although they do fail to distinguish between elements of distributed cognition and extended cognition within them (Amon & Favela, 2017). These three cases are all technical or scientific institutions, however, and may not be applicable to the wide range of human social setups (Neemeh & Favela, forthcoming).

This chapter studies three human social systems for evidence of distributed cognition, swarm intelligence, or superorganismic cognition using the previously established criteria. These include small groups, crowds, and entire societies. These cases are presented as a progressively-widening series of human social systems. That is, small groups are preceded by the much larger crowd phenomenon, in turn preceded by societies in their entirety. This is done in order to push

outward the bounds of what are considered to be cognitive phenomena. Crowds and societies prove to be particularly complex and complicated cases, with inconclusive evidence. Consequently, they are presented as open cases to direct future research.

4.2 Small Groups

4.2.1 Evidence. Small human groups have at least two members, but their upper bound is fuzzy. They are here defined as two or more humans collected in the same, continuous space that is small enough to maintain personal contact between the members. It may not be proper to consider a single numerical upper limit for the individuals constituting a small group. Their size may vary with context. Examples of small groups include couples, several friends together, a small study session, and an orchestra. A corporation or an educational institution does not count, as they are divided into separate rooms, buildings, cubicles, or even campuses. A large group collected into a single, continuous space is no longer able to maintain personal contact between its members and is instead a crowd.

Groups of four individuals (ABCD) arguing over a highly controversial topic (abortion) were studied by Lisiecka (2013). Emergent patterns of interaction were found according to whether the groups agreed or disagreed. Patterns of interaction wherein two individuals engaged back-and-forth (and ABAB pattern) was indicative of strong disagreement, independent of the content of the conversation. Other patterns of interaction (ABAC, ABCA, ABCB, or ABCD) were less associated with heated debate and polarization. The overall patterns of interaction within the groups of four were emergent.

The smallest human groups are composed of only two members. Intimate couples are one prominent example of such a group persisting over an extended period of time (months, years, or decades). Groups collaborating together typically show a marked deficit in memory over individuals. This effect is known as collaborative inhibition and its effects are persistent over different types of groups (Harris, Barnier, Sutton, & Keil, 2014). While some intimate couples are also subject to this effect, others' memory recall instead improves when working in concert. Not all intimate couples are equally collaborative, empathetic, or involved with one another, and this is not a surprising find.

Notably, couples themselves tend to shift their use of pronouns from "I" to "we" when collaboratively remembering. Higher use of the first person plural pronoun is correlated with more rapid collaboration. Episodic memories are enhanced in some older *couples*, while they generally decline in older *individuals*. Colloquially, it is said that someone "jogs" another's memory. This assumes that the memory is stored as a complete whole within the other's mind. This folk psychological description is misleading, at least in the case of couples. These episodic memories are emergent insofar as they are constituted by the interaction of the two individuals (Harris, Barnier, Sutton, & Keil, 2014). Neither person individually remembers all of the details of the episode, but they together recall a shared memory. An example best serves to illustrate this common phenomenon, and it will probably strike the reader as familiar. The interviewer asks a couple about their early courtship:

"Husband: No, I asked her out that night, but she said she couldn't go.

Wife: No, that's right.

H: So then I started to pester her the next week.

W: You did, you turned up after my classes.

H: Cooking classes.

W: On Monday night.

H: That'd be it.

W: And took me for coffee.

H: Yes, the next Monday night.

W: And impressed me.

H: Yes" (Harris et al., 2014, p. 292).

Different accounts of the same episodes are given when the same individuals qua individuals are asked to recall them (Harris et al., 2014). Not only are they attenuated, but the individuals emphasize different details. Compare the previous emergent remembrance with the following. The same couple was earlier asked the same question individually. Their accounts are markedly less fluent, less distinct, less precise, and do not emphasize the same details. Note that they are presented serially but are not responding to one another:

"Husband: Ah, I used to turn up...down her...she used to give, umm, what do you call it, teaching, she used to teach, umm, women in Manly how to cook. So she ran teaching classes. So I used to turn up there after, and take her out for coffee or something.

Wife: And then the next week he appeared at my work after the evening class had finished, taking me out for coffee – that was the beginning of the courtship"
(Harris et al., 2014, p. 292).

4.2.2 Small groups as distributed cognition. Small groups are best understood as distributed cognitive systems. Distributed cognition was developed primarily to explain technical-scientific institutions. Nevertheless, it is not limited to such situations, as the case of wolf packs made clear. Small groups exhibit emergent behavior (D1), such as conversational patterns and collective remembering (Lisiecka, 2013; Harris et al., 2014). They are themselves not necessarily emergent organizations, however. Although some small groups form spontaneously or without planning, many are assigned together by commands or institutional structures. There is a continuous coordination of members of the small group (D2). In the above examples, this coordination was linguistic rather than locomotive or spatial. More items are able to be coordinated because of the greater complexity of human individuals. The couple seamlessly and fluently remembered the event of their first meeting, each taking turns in adding more details and completing the memory. In Lisiecka's (2013) study of patterns of disagreement, the individuals likewise continuously engaged one another in dialog.

Each member of the small group maintains a strong degree of individual agency (D3). Individuals in a small group do not become overwhelmingly subordinated by it, even in the presence of peer pressure or other influencing factors. The conversations between individuals are relatively free and individuals are not compelled by any internal necessity to continue their conversations (although extraneous necessities may constrain them to in some cases, such as a jury being forced to come to a decision by the court).

Each member actively participates in the overall goal or joint task in which the small group is engaged (D4). In the examples, this joint task is remembering or debating a point of controversy. There is a specialization of functions among the members of the small group (D5).

This specialization of functions may be well-developed or rudimentary. Well-developed specialization of functions include positions of leadership and dominance. More rudimentary specialization of functions can be noted in the example of the couple reminiscing. There is a primary responder and a secondary responder. The primary responder is the person to whom the question is addressed, and the secondary responder is the other member of the couple who assists the first with recalling the episodic memory. Finally, the cognitive behavior of the small group is complex and is not limited to perception and action (D6). The linguistic capacities of individuals can be fully exercised within the small group in ways that is not possible with exponentially larger groups. The group is small enough that individuals are able to give their full attention to one another. Small groups fulfill SI1-6 and are thus best thought of as distributed cognitive systems.

4.3 Crowds

4.3.1 Evidence. Crowds are large groups of humans collected together in one continuous space. There is no precise numerical definition of how many individuals constitute a crowd. The salient distinction is that the group must be too large to permit personal contact between its members. This contrasts with small groups, wherein more personal and intimate communication is able to take place. Examples of crowds include a music concert audience, a large group stampeding during the Hajj, a mass of people running out of a burning building, or a peloton (a massive group of cyclists). The seated audiences of theaters, orchestras, operas, and other performances are crowds when they act in concert, such as clapping. They do not constitute

crowds when they are sitting individually disengaged from group behavior. Moussaid and colleagues (2009) classify crowds as instances of distributed cognition primarily because they are self-organized rather than heteropoietic. This is not a sufficient condition for distributed cognition, however, and is shared by swarm intelligence and superorganismic cognition. It is the same paucity of concepts of social cognition that leads them to this erroneous classification as led O'Donnell and colleagues (2015) to a similar classification of wasps. Trenchard (2015) classifies the peloton as a superorganism. Once again, this term is used imprecisely. It appears that terms like 'distributed cognition' and 'superorganism' are sometimes loosely applied to describe any cognition transcending the individual.

As with bird flocks evading a raptor, not all of the individuals constituting the crowd may be aware of the salient information guiding the collective as a whole. Dyer and colleagues (2007) tested students in a circle, most of whom were uninformed or "naïve" and a minority of which were informed (given a target). The movement of the entire group converged upon the targets previously made known to the informed individuals. Nevertheless, these individuals cannot be said to have been explicit leaders or guides. They did not communicate intentions or otherwise direct naïve individuals. Rather, the convergence upon the target was an emergent effect of the movement of the group as a whole. This is analogous to the local group of birds in a flock that actively seek to evade a predating hawk. Most birds do not necessarily perceive the predator, but an evasive behavior nonetheless emerges in the flock (Neemeh & Favela, under review).

More dispersed crowds, such as large numbers of pedestrians flowing through a city, share with ants a form of stigmergic communication. One way stigmergic path formation can operate is by the gradual physical imprinting of paths in the ground (Moussaid et al., 2009). This

process is slow and does not represent crowd behavior. Within cities, however, similar mechanisms of stigmergic communication and path formation appear. Using Ant Colony Optimization (ACO), Kheiri (2016) simulated the flow of pedestrians in through the busy Honarmadan Park in central Tehran. Pedestrian flow is organized around six separate entrances and is structured around individuals' perceptions of others' locations and movements. Moussaïd and colleagues (2009) further note that pedestrian flows spontaneously organize into two lanes, although there is a cultural contribution to this phenomenon as well.

4.3.2 Towards a classification of crowds. Crowds express similar properties to swarm intelligence, but they diverge from this class in several respects. Crowds are self-organizing and emergent (SI1). When moving across discrete paths, they display stigmergic communication (Kheiri, 2016; Moussaïd et al., 2009), a form of self-organized and emergent behavior (Hölldobler & Wilson, 2009). In more amorphous crowds, principles similar to the mechanisms of repulsion and attraction keep the mass bound together. There is a continuous coordination of individuals as members of the crowd (SI2). This coordination can include direct, verbal and nonverbal communication, however. In this respect, they diverge from systems such as schools of fish or bird flocks.

Individual agency can be but is not necessarily minimal insofar as the individual constitutes the crowd (\neg SI3). In very large crowds, such as a stampede, there is little opportunity for any other behavior aside from running in the direction of the crowd flow. In more open and dispersed crowds, however, there is ample opportunity to autonomously switch directions or

disengage from the crowd. The cognitive behavior of the crowd is *not* limited to perception and locomotion (\neg SI4).

Communication or interaction between members of the crowd is minimal but there is a communication of intentions (\neg SI5). There may be a communication of intentions in crowds, although the entire crowd does not necessarily have to share the intention. A few individuals may shout “fire!” in a building and a stampeding crowd may ensue. Many of the individuals may share an intention of ‘fire.’ Nevertheless, as Dyer and colleagues (2007) have shown, crowd behavior can manifest without any such shared intentions. Although crowds can operate without shared intentions, here they differ from other swarm intelligent systems.

The organization of the crowd is relatively isomorphic. There is no specialization of functions between the members of the crowd (SI6). In Dyer and colleagues’ (2007) study, the informed individuals were not leaders. They acted by the same locomotive principles as their fellow naïve participants. They are only called “leaders” in a loose sense, as with “leader” birds in a flock. The only difference between informed and naïve individuals is that the former have an intention not shared with the latter. This situation also obtains in crowds fleeing burning buildings. A few informed individuals may “lead” the rest of the crowd towards the exits. Crowds are closest to swarm intelligence but they do not completely fulfill SI3-5. Given their similarities to swarm intelligent systems, however, there is strong evidence that they may be social cognitive systems. It remains to be determined how to precisely understand cognition in these systems.

4.4 Societies

Societies are the largest collections of humans. They can range from hamlets, villages, towns, cities, and megalopoleis to entire nations or civilizations. It is not entirely clear if any of these societies operate on some level as unified cognitive systems. It is possible they are merely networks of smaller cognitive systems. A city, for example, is possibly a network of thousands or millions of individuals, small groups, crowds, institutions, and technical-scientific institutions in the vein of Giere's (2006) HST. DeLanda (2000) argues cities operate as complex systems built on top of older, more "primitive" structures such as natural processes of mineralization. Even if DeLanda is correct, this is only a necessary and not a sufficient condition for social cognition. Many complex systems are not cognitive, such as hurricanes, tornados, and galaxies (Parrish, Viscido, & Grünbaum, 2002).

Lisiecka (2013) similarly notes there are multiple, coexistent levels of emergent order, or a supervenience of levels: atoms, molecules, individuals, living systems, and groups. On the group level, these emergent orders include group culture, memory, social practices, and conversational routines. Sawyer (2005) adds to this list language shifts over time, and Nowak and colleagues (2013) add opinions, attitudes, politics, religions, fashion, and farming techniques. These analyses of complexity in societies are all of specific elements constituting societies. Within social psychology itself, there are few unified theories and most consider isolated elements within societies (Nowak, Vallacher, Strawińska, & Brée, 2013). Although these social elements are to a degree conceptually and experimentally isolable, they ultimately are inextricable from the broader society to which they belong.

“Most social properties are nonaggregative, many social systems are not decomposable, most are not functionally localizable, and all depend on symbolic communications that use the full richness of human language” (Sawyer, 2005, p. 99).

It is this symbolic communication that significantly makes societies differ from collective biological systems. In crowds, there may be a minimum of symbolic communication and this may aid in the construction of collective intentions (e.g., “fire!”). In societies, however, symbolic communication is at the apex of its complexity. Integrating the intricacies of language into a social cognitive paradigm is a formidable task and is well beyond the scope of this study.

Kesebir (2012) classifies societies as partial superorganisms and even likens them to slime molds (see Bonner & Raper, 1976). Unlike in ant colonies, other eusocial insect swarms, or slime molds, however, individual humans’ agency is strongly preserved in societies. Sawyer (2005) suggests they have features akin to swarm intelligence. Their behavior extends far beyond the confines of perception and locomotion, however. Of the three types of social cognition presented in this study, societies are closest to distributed cognition. They are emergent (D1; DeLanda, 2000; Lisiecka, 2013; Nowak et al., 2013; Sawyer, 2005). It is not clear how to answer the second criterion, however (\neg D2). Is there a continuous coordination of agents and nonagentic tools as members of the society? What would it even mean for the components of a society to be continuously coordinated? Each agent does, however, maintain a degree of individual agency within the society (D3). In considering the fourth criterion, once again it is unclear how this would be applied to societies (\neg D4). Does each agent actively participate in the overall goal or joint task in which the society is engaged? DeLanda indicates that there are society-wide behaviors, such as the expansion of a city according to its geographical situation

(2000) or integration into a new nation by conquest (2006).¹⁵ Can such behavior be said to be a joint task, perhaps unrecognized by individuals in a similar way to ants building a nest? Here, it is perhaps even more a lack of an adequate philosophical vocabulary and conceptual clarity than a lack of empirical studies that makes this question unanswerable.

The final two criteria are easier to analyze. There is a very pronounced specialization of functions among members of societies, including professional, governmental, familial, and other roles (D5). Finally, the cognitive behavior of societies is complex and not limited to perception and locomotion (D6). Societies build infrastructure, buildings, institutions, factories, and other cultural artifacts. Several of the criteria, however, are—within the terms of the theory presented—simply unanswerable either affirmatively or negatively.

The evidence for societies, including hamlets, villages, towns, cities, and megalopoleis, is far less conclusive than that for crowds. The difficulty with crowds was in introducing collective intentionality. It is a well-defined problem that future research can directly address. For societies, there is a far stronger lack of conceptual clarity. Instead of clear problems, we can at this point only pose suggestive questions. We are only at the beginning stages of the exploration of societies as cognitive systems. Dynamical social psychology (Nowak et al., 2013), dynamical systems sociology (Sawyer, 2005), and Material Engagement Theory (Malafouris, 2013) are on the frontiers of this new exploration. Are societies cognitive systems, or are they merely complex systems? Are they networks of interconnected individuals, small groups, crowds, and

¹⁵ Memphis, TN, for example, historically grew northeastwards in a diamond shape because of its location at the corner of the Mississippi River and the state of Mississippi.

institutions? Or do they have an ontological status in their own right? Ultimately, an adequate philosophical vocabulary must be constructed to be able to answer these many questions.

CHAPTER 5: CONCLUSION

5.1 Cognition Is a Property of Group and Social Systems

A preliminary taxonomy of social systems with criteria was developed with three types: distributed cognition, swarm intelligence, and superorganismic cognition. Two series of cases across collective biological and human social systems were analyzed according to the previously established criteria. This division is practical and is not indicative of any absolute differences. Wolf packs and small human groups are cases of distributed cognition. Bird flocks, schools of fish, and human crowds are cases of swarm intelligence. Eusocial insect swarms are cases of superorganismic cognition. By establishing criteria of different types of social cognitive systems, these vastly different phenomena can be compared with one another. The categories themselves may not be absolutes, and there may very well be some slippage among them. They are intended to be pragmatic, exploratory descriptors rather than exhaustive accounts. Common to them all is a global-level cognition that emerges from the local interactions of organisms in the collectivity.

The perception and movement of individual birds within a flock cannot simply be understood as a function of the individual, even in reference to its neighbors. For the individual bird is part of a dynamical system fluctuating in time and curling, pullulating, and whirling like a wisp of smoke. In order to understand its local behavior, the global behavior of the flock must be understood. The cognitive behaviors of the ant, too, are better understood nonreductively. To understand how the individual ant with its miniscule brain ended up at the food source, the emergent effects of stigmergy in the swarm must be understood. Likewise, to understand why an ant is defending an aphid from attack by a ladybug, both the ant's and the aphid's place in the

structure of the swarm must be understood. For wolves, the convergence of several wolves on a prey animal can only be understood as a group function. Schools of fish, like bird flocks, emerge as collective units through the local interactions of individual fish. In small human groups, individuals work together to achieve goals and express emergent cognition in doing so. Crowds function by much the same processes as bird flocks and schools of fish. A leader does not control them, but their actions emerge through the local interactions of neighboring individuals.

Therefore, in collective biological and human social systems—including bird flocks, eusocial insect swarms, wolf packs, schools of fish, small human groups, and human crowds—cognition is an emergent property irreducible to the sum of the cognitions of the member organisms. To understand a single organism’s cognition within the context of these collectivities necessitates a systems approach. This is not to deny that individuals have cognition qua individuals. This is especially apparent with human individuals in a crowd, which are individually quite complex cognitive systems unto themselves, but together constitute a markedly simple cognitive system.

5.2 Expanding the Bounds of the “Cognitive”

For CRUM, cognition begins and ends at the brain or nervous system. 4EA approaches have expanded those boundaries to phenomena as small as the individual cell and as large as the organism-environment system. A consequence of this study is the further expansion of the outer bounds of cognition. This work is intended to motivate future research into further cases of social cognition and additional types of social cognitive systems. The series of case studies presented is by no means exhaustive and similar social cognitive systems surely exist. They are merely

particularly well-researched cases. Further cases may not all fit into the threefold taxonomy here devised. This taxonomy was presented programmatically in the hope that more types of social cognitive systems will be discovered. Possessing a wide range of concepts of social cognition is an indispensable tool to exploring the outer bounds of cognition.

In this study, the status of crowds and societies was not decisively determined. Suggestions for further research are given to guide those first steps into exploring further cases of social cognition and types of social cognitive systems. Evidence is given that they may be cognitive systems, but it remains to be determined. If they are indeed cognitive systems, it must be resolved whether they are unified systems or rather a network of smaller social cognitive systems. For societies, there particularly lacks a conceptual clarity that must be addressed by future philosophical work.

Human societies are possibly cognitive, but the outer bounds of cognition find their absolute limit at the Earth as a unified, homeostatic system. Lovelock's (2000) Gaia may share certain features with cognitive systems, such as homeostatic mechanisms and emergent behavior. Nevertheless, emergence in itself is not a sufficient condition for cognition. Tornados, galaxies, and hurricanes are also emergent systems and bear striking similarities to some animate formations (Parrish et al., 2002), but that does not make them cognitive. There exists a deep and profound mathematical unity between these physical phenomena and cognitive phenomena that dynamical systems theory is only beginning to uncover. Self-organizing criticality (SOC) is possibly the holy grail of systems theory that Ludwig von Bertalanffy (1968) searched for and

may be a fundamental organizational principle of the universe.¹⁶ Nevertheless, despite Lovelock's sometimes romantic metaphors, Gaia has no more faculty for perception-action than galaxies or tornadoes. The noosphere is at least as broad as collective biological and human social systems, perhaps as expansive as entire human societies, and not as large as the Earth as a unified system. It remains to be determined *precisely* where the outer boundaries of the noosphere lie.

5.3 Towards a Renewed Relevance of the Social Sciences in the Cognitive Sciences

A corollary consequence of the expansion of the scope of cognition is the renewed relevance of the social sciences within the interdisciplinary matrix of the cognitive sciences. In 1978, the six-pronged interdisciplinary wheel of the cognitive sciences was first published (see Figure 4; Sloan Foundation). Since then, the relevance of anthropology has tapered off and is only given a passing acknowledgement or a symbolic nod in the cognitive sciences (Hutchins, 2010; Thagard, 2010). This study suggests that the social sciences, including anthropology and sociology, have a renewed relevance to the cognitive sciences. The old idea of incorporating anthropology was to incorporate cross-cultural perspectives into cognitive models. This would escape the trap of naively studying the Western individual as if they were the *universal* individual. The new idea is that groups and societies themselves are actually relevant objects of study. Small groups, crowds, and possibly societies are nonreductive social cognitive systems. This also expands the potential contribution of biology to the cognitive sciences to also include

¹⁶ See Jensen (1998) for SOC in physical systems and biological evolution and Favela (forthcoming) for SOC in the cognitive sciences.

sociobiological work on flocks, swarms, colonies, and other such emergent group entities (Hölldobler & Wilson, 2009).

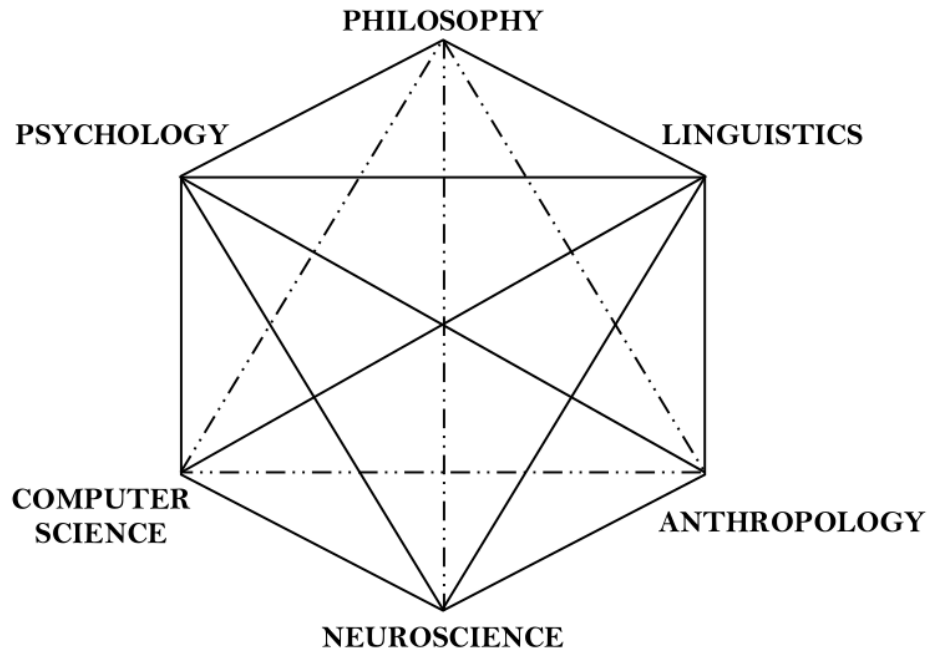


Figure 6. The interdisciplinary matrix of the cognitive sciences. After Sloan Foundation (1978).

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